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ENVIRONMENTAL FACTORS AND THE EPIDEMICS OF COVID-19

Role of knowledge, behavior, norms, and e-guidelines in controlling the spread of COVID-19: evidence from Pakistan

Ali Raza[1] · Qamar Ali[2] · Tanveer Hussain[3]

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Abstract

The COVID-19 pandemic is straining public health systems and the global economy, triggering unprecedented measures by governments around the globe. The adoption of a preventive measure is required to control the spread. This research explores the impact of influencing factors like COVID-19 knowledge, behavioral control, moral and subject norms, preventive e-guidelines by the government, and environmental factors on the intention to prevent COVID-19 and risk aversion. A cross-sectional study was performed of 310 respondents about different COVID-19 related influencing factors in Pakistan. The partial least square-structural equation modeling was applied to estimate the path coefficient. Moral and subject norms (0.359) had a comparatively higher path coefficient. Other influencing factors/drivers were preventive e-guideline by the government (0.215) followed by COVID-19 knowledge (0.197), and behavioral control (0.121). The intention to prevent COVID-19 showed a positive and significant impact (0.705) on risk aversion. The indirect analysis also confirmed that the positive influence of moral and subject norms, COVID-19 knowledge, preventive e-guideline by the government, and behavioral control on risk aversion. However, the path coefficient of environmental factors was negative but insignificant, which implies than environmental factors do not influence the intention to prevent COVID-19. It is suggested to provide clear guidelines using print, social, electronic media. It is also suggested to provide e-guidelines in local languages. The COVID-19 knowledge about its transmission, symptoms, and precautions is also useful. It is suggested to include the causes, symptoms, and precaution of viral diseases in the educational syllabus. The government should ensure the availability of preventive medical items like surgical masks and sanitizers to meet the demand of the public.

Keywords Behavior · Environment · COVID-19 knowledge · Pandemic · PLS-SEM · SARS-CoV-2

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✉ Tanveer Hussain
tanveer.hussain@vu.edu.pk

Ali Raza
maharalirix44@gmail.com

Qamar Ali
qamarali2402@gmail.com

1 Department of Molecular Biology, Virtual University of Pakistan-Faisalabad Campus, Faisalabad 38000, Pakistan

2 Department of Economics, Virtual University of Pakistan-Faisalabad Campus, Faisalabad 38000, Pakistan

3 Department of Molecular Biology, Virtual University of Pakistan, -54000, Lahore, Pakistan

Introduction

The epidemiological dynamics of many infectious diseases depend upon environmental factors (Shi et al. 2020). The Severe Acute Respiratory Syndrome (SARS) was linked with environmental factors (Sobral et al. 2020). Epidemiological research explored the association between coronavirus and meteorological indicators but the findings were not clear (Wu et al. 2020). Coronaviruses named due to their spherical and pleomorphic outer fringe resembling crown (“corona” in Latin) belongs to the family of enveloped Ribonucleic acid (RNA) viruses (Burrell et al. 2016). The novel coronavirus accountable for the current outbreak is called 2019-nCOV while the disease is called as COVID-19 (Carico et al. 2020). The COVID-19 pandemic emerges as a viral outbreak of a new virus, which was first reported in the Wuhan, Hubei in China on December 08, 2019 (Deng and Peng 2020). The novel Coronavirus was named as Severe Acute Respiratory

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Syndrome Coronavirus 2 (SARS-CoV-2). The World Health Organization (WHO) declared the COVID-19 outbreak as the 6th public health emergency following H1N1 (2009), polio (2014), Ebola in West Africa (2014), Zika (2016), and Ebola in the Democratic Republic of Congo (2019) (Lai et al. 2020).

Some studies (Gale et al. 2010; Stott 2016) mentioned that climate change was linked with the emergence and spread of various infectious diseases. Literature showed that cold and dry weather is favorable for the transmission of droplet-mediated viral diseases like influenza. The SARS epidemic was decreased with the warming weather and ended in July 2003. The COVID-19 pandemic was mostly observed in the countries, located in low-temperature regions (Liu et al. 2020). Analyzing 166 countries, Wu et al. (2020) reported that the 1 °C rise in temperature was responsible for 3.08% and 1.19% reduction in daily cases and daily deaths, respectively. On the other hand, 1% rise in relative humidity was responsible for 0.85% and 0.51% reduction in daily cases and daily deaths, respectively. Researchers reported that the weather indicators explain 18% of the variation in disease doubling time, while 82% variation was linked with general health policies, containment measures, transportation, population density, and cultural aspects (Oliveiros et al. 2020). It is also required to develop coordination between the general public, health workers, and governments to control its spread (Lai et al. 2020).

The COVID-19 becomes a major threat to public health as well as the global economy, which also affects the lives of human beings. The COVID-19 was responsible for the feelings of panic anxiety and depression (Jiao et al. 2020). They are pathogenic to mammals and birds and cause mild upper respiratory tract infections in human beings. They can cause severe respiratory illnesses exemplified by SARS and Middle-East Respiratory Syndrome (MERS) that emerged in 2003 and 2012, respectively (Roy et al. 2020). The communities have been directed to stay at homes, frequently wash their hands, avoid gatherings, and maintain 1–2 meter distance from others (social distancing), and avoid touching their face to break the COVID-19 spread (Carico et al. 2020).

The novel coronavirus seems to be originated from an animal origin as the majority of the reported patients were being dealers and vendors in the Huanan Seafood Market (Roy et al. 2020) but the origin of this virus is not yet evident. The COVID-19 has caused a substantial number of deaths worldwide, posing a serious threat to public health in the world (Li et al. 2020). Along with the implacable socio-economic impacts of this pandemic, the escalating mortality and morbidity is a problem. The WHO reports that the mortality rate was between 3 and 4% (Baud et al. 2020). From December 29, 2019, through July 21, 2020, COVID-19 infected 14,348,858 people globally, which results in 603,691 causalities with a mortality rate of 4.21% (WHO 2020).

The first COVID-19 patient in Pakistan was confirmed on 26th February 2020 in Karachi, which is ranked as a populous city in the country. This patient had a travel history to Iran. After that, the increase in COVID-19 patients has been observed in Pakistan (Syed and Sibgatullah 2020). The coronavirus confirmed cases until July 21, 2020, were 266,096 with 5639 death and 208,030 recovered patients (Government of Pakistan 2020) (Fig. 1). The WHO has already declared that Pakistan is facing a crisis during this pandemic. It has the potential to worsen the national health condition and socio-economic infrastructure of the country even more if it does not act on time. The WHO expressed its fear that if necessary precautionary measures are not adopted to mitigate this pandemic, Pakistan might be the next hub of the pandemic. It is supposed that the community perception about the risk of this infection is not affirmative and they are not giving adequate considerations to the epidemic preventions. The Ministry of Health, Pakistan has proclaimed new guidelines for virus control which are based on the WHO recommendations (Khan et al. 2020).

The adoption of a preventive measure by the general public is very important to control the spread of epidemics. There are gaps in pandemic knowledge and preparedness among the population due to disparities in the transmission of information and access to the media. Research on knowledge and behavior in the case of a pandemic is helpful in the communication and mitigation policies (Johnson and Hariharan 2017). Guiding the general public to undertake health safety behaviors is proved useful to control infectious disease. However, motivating the public to adopt preventive behaviors is difficult. Literature showed that people may follow health-related suggestions if they thought that recommendations are effective (Rubin et al. 2009).

In the case of the current pandemic, the implication of the personnel protective measures is only feasible if the community is well aware of the COVID-19 knowledge and responds positively towards the preventive e-guidelines by government. To combat the COVID-19, it is required that the people have the intention to adopt precautionary measures. However, the intention to adopt precautionary measures and risk aversion may be influenced by multiple factors. These factors include COVID-19 knowledge, behavioral control, moral and subject norms, preventive e-guidelines by the government, and environment.

There is a paucity of research that evaluated the impact of COVID-19 knowledge, behavioral control, moral and subject norms, preventive e-guidelines by the government, and environmental factors on the intention to prevent COVID-19 and risk aversion. Therefore, this research tries to fill the research gap by considering these influencing factors in the context of Pakistan.

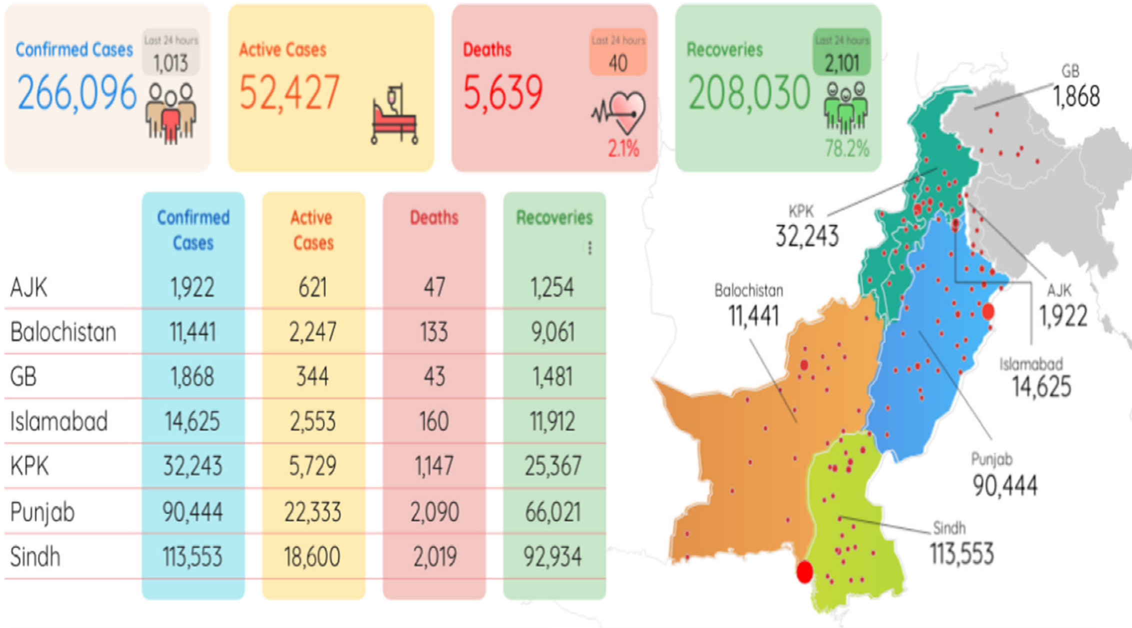


Fig. 1 Current statistics of COVID-19 in Pakistan, on July 21, 2020 (GOP 2020)

Review of literature

Different cross-country studies explored the role of knowledge, norms, attitude, and behavior for the prevention of diseases. After the COVID-19 outbreak, different studies examined the relationship between COVID-19 knowledge, attitude, preventive practices, and intention to adopt preventive behavior in different countries. Angelillo et al. (2000) explained the role of knowledge, behavior, and attitudes in the case of foodborne diseases in Italy. About 48.7% food handlers knew the foodborne pathogens (*Staphylococcus aureus*, *Salmonella* spp., *Clostridium botulinum*, *Vibrio cholerae* or other *Vibrio* spp., hepatitis A virus). The knowledge of foodborne pathogens was positively correlated with the higher education level. More than 90% respondents knew the foods, responsible for foodborne diseases. Only 20.8% respondents used gloves when touching unwrapped raw food. To control foodborne diseases, they recommended the need for educational programs for the increase in knowledge. Mulligan et al. (2006) compared the HIV knowledge, behavior, and attitudes/beliefs among dental health professionals before and after the completion of a course in the United States. A significant change in HIV knowledge (65%), behavior (55%), and attitudes/beliefs (86%) was reported among the participants. Therefore, the educational program was found beneficial for the increase in HIV/AIDS knowledge and attitudes/beliefs among health professionals. Souza et al. (2016) stated that the risk of hepatitis C virus infection was higher in dental health professionals. They evaluated the HCV infection knowledge and attitude of dental students in Brazil. More than 50% respondents had HCV knowledge above the mean score. The positive attitude was reported in 97.7% dental students. The HCV knowledge was significantly influenced due to an increase in the year of study. Age and male gender were two influencing factors behind the positive attitude towards HCV infected patients.

Chesser et al. (2020) described the COVID-19 knowledge, beliefs, and role of social media during health crises in the United States. About 43% of students confirmed a high level of health literacy. The majority of students heard about COVID-19 pandemic through the internet and social media. Mostly students had basic COVID-19 knowledge while only 18% of students knew all symptoms of COVID-19. Hayat et al. (2020) stated the importance of public awareness about COVID-19 symptoms, cleanliness, and transmission mode to implement effective health policy. They examined the perspective of the public about COVID-19 knowledge, practices, and attitude in Pakistan. More than 60% of respondents had good knowledge of COVID-19. Moreover, COVID-19 knowledge was significantly related to education, gender, and marital status. About 77% of respondents believed that COVID-19 would be successfully controlled in Pakistan. More than 85% of respondents used a face mask for their protection while frequent hand wash was reported by more than 88% of respondents. Azlan et al. (2020) mentioned the lockdown and movement control policy to control the COVID-19 spread. They examined the role of COVID-19 knowledge, practices, and attitudes to ensure the readiness of Malaysian society to accept the mitigation measures. More than 80% of respondents had COVID-19 knowledge. Many participants followed preventive measures like avoid crowds (83.4%) and hand wash (87.8%). Surprisingly, only 51.2% of participants used face masks in Malaysia.

Kebede et al. (2020) assessed COVID-19 knowledge, practices, and perceptions in Ethiopia using logistic regression. More than 80% of respondents knew clinical symptoms. About 72% of respondents think that the risk of COVID-19 was higher for older people who have chronic illnesses. More than 90% believed that the respiratory droplets of an infected person were a factor behind COVID-19 spreads. To prevent COVID-19, avoid handshake (53.8%) and frequent hand wash (77.3%) were also reported by the respondents.

Clements (2020) described the influence of COVID-19 knowledge on participation in different behaviors such as the use of medical masks, the purchase of more goods, and presence in large gatherings in the United States. The reduction was observed in the use of face masks (44%), purchase of more goods (12%), and presence in large gatherings (13%) for every point increase in COVID-19 knowledge.

Zhang et al. (2020 analyzed COVID-19 knowledge, attitude, and practices during the COVID-19 pandemic among healthcare workers in China. About 89% of healthcare workers had sufficient COVID-19 knowledge while 85% of healthcare workers feared self-infection with the virus. Approximately 90% of healthcare workers adopted the recommended practices during this pandemic. The risk factors like job category and work experience also influenced the practice and attitude of healthcare workers.

Dryhurst et al. (2020) wrote that COVID-19 transmission is influenced by the willingness of people to adopt preventative behavior. They assessed the risk perception of COVID-19 in 10 countries from Asia, Europe, and America. The levels of concern were comparatively more in the United Kingdom. The significant predictors of risk perception were personal COVID-19 experience, hearing about COVID-19 from friends, individualistic and prosocial values, trust in government, personal and collective efficacy, medical and science professionals, and knowledge of government strategy. A significant correlation was reported between risk perception and the adoption of preventative measures in all ten countries.

Zhong et al. (2020) revealed the behavior of Chinese residents during the COVID-19 pandemic, which was influenced by COVID-19 knowledge, practices, and attitudes. About 90% of respondents had correct knowledge of COVID-19 while 97.1% of respondents believed that China can win the battle against COVID-19. The majority of respondents (98.0%) used a face mask when going out. The COVID-19 knowledge score was significantly linked with a lower likelihood of negative attitudes and preventive practices.

Therefore, this study extended the literature and assessed the influence of COVID-19 knowledge, behavioral control, moral and subject norms, preventive e-guidelines by the government, and environmental factors on the intention to prevent COVID-19 and risk aversion.

Methodology

Data and study area

This study based on primary data about different COVID-19 related measuring instruments, which may influence the intention to adopt preventive measures and risk aversion in Pakistan. To empirically investigate the research objective, this study used an online survey using a structured questionnaire. The participants in this study answered COVID-19 related questions on a five-point Likert scale, indicating 5 for strongly agree, 4 for agree, 3 for uncertain, 2 for disagree, and 1 for strongly disagree. Data collection was collected using online sources from April 1, 2020, to April 14, 2020. A total of 310 respondents answered the questions which belong to different age groups, gender, educational qualification, and occupation. The sample size is appropriate to perform a partial least square-structural equation model because the cut-off sample size was 100 (Reinartz et al. 2009; Rasoolimanesh et al. 2018).

Measuring instruments and hypothesis

Due to COVID-19 transmission in the world, it is important to adopt different risk aversion measures. To control COVID-19, it is also required that the people have the intention to prevent COVID-19. However, the intention to prevent COVID-19 and risk aversion may be influenced by multiple factors. Therefore, this research investigates the impact of knowledge about COVID-19 (COK), behavioral control (BC), moral and subject norms (MSN), preventive e-guidelines by the government (PEG), and environmental factors (EF) on the intention to prevent COVID-19 (IPC), and risk aversion (RA). These influencing constructs were measured using different related questions. The intention is influenced by perceived behavioral control, subjective norms, and attitudes towards the behavior (Dumitrescu et al. 2011). Based on the selected constructs, this study tried to confirm the following hypothesis:

Knowledge and beliefs influence the behavior-specific self-efficacy, goal congruence, and outcome expectancy (Ryan 2009). Higher knowledge is likely to be linked with more risk perception (Aerts et al. 2020). Lei et al. (2019) examined the preventive measures, knowledge, and attitude of poultry market workers in China. They confirmed that the less knowledge was responsible for insufficient preventive measures. Therefore:

> H_1: Knowledge about COVID-19 is expected to have a positive impact on the intention to avoid COVID-19.

H_2: Knowledge about COVID-19 is expected to have a positive impact on risk aversion.

Blue (2007) confirmed the influence of behavioral control on the intention of diabetic patients to take healthy foods and engage in physical activities. Msn and Kang (2020) also reported the significant influence of perceived behavioral control on the intention of nurses to look after patients in Korea. The perceived behavioral control was a substantial factor to prevent SARS in Singapore, Toronto, and Hong Kong (Cheng and Ng 2006). Therefore:

H_3: Behavioral Control is expected to have a positive impact on the intention to avoid COVID-19.
H_4: Behavioral Control is expected to have a positive impact on risk aversion.

The behavioral intention was also influenced by the subjective norms, which is a person's perception that people who are important to him (or her) think he (or she) should or should not perform the behavior in question. Subjective norms are determined by normative beliefs and the motivation to comply with specific referents (Kan and Fabrigar 2017). Moral norms are influential factors behind preventive attitude. Investigating the relationship between moral norms and tobacco usage, Sorensen et al. (2005) revealed that tobacco use was more in Bihar, India because moral and social norms strongly encouraged the use of tobacco. Therefore:

H_5: Moral and subject norms are expected to have a positive impact on the intention to avoid COVID-19.
H_6: Moral and subject norms are expected to have a positive impact on risk aversion.

The role of media is also important for the infectious disease, as it can decrease the probability and opportunity of contact transmission among the susceptible populations, which further control and preventthe spread of disease (Cui et al. 2007). Social media can promote self-care, emphasizing the curative and preventive measures for disease (Islam et al. 2019). Therefore:

H_7: Preventive e-guidelines by the government are expected to have a positive impact on the intention to avoid COVID-19.
H_8: Preventive e-guidelines by the government are expected to have a positive impact on risk aversion.

Literature (Gale et al. 2010; Stott 2016) explored the association between climate change and the spread of infectious diseases. Cold and dry weather is favorable for the spread of droplet-mediated viral diseases like influenza. The SARS epidemic was decreased with the warming weather and ended in July 2003 (Liu et al. 2020). The use of face masks is important for the protection of health care workers in hospitals and can reduce the spread of the pandemic infection like COVID-19. Scarano et al. (2020) reported the increased facial skin temperature, lower wearing adherence, and greater discomfort due to the use of an N95 mask as compared with the medical-surgical masks. Therefore:

H_9: Environmental factors are expected to have a negative impact on the intention to avoid COVID-19.
H_{10}: Environmental factors are expected to have a negative impact on risk aversion.

Risk-averse individuals will face a "risk-elastic demand for prevention": a percentage increase in the risk will lead to a greater percentage increase in self-protective behavior (Aerts et al. 2020). In general, it is assumed that people would normally make rational decisions to avoid risks (Nomura et al. 2004). Therefore:

H_{11}: Intention to prevent COVID-19 is expected to have a positive impact on risk aversion.

Econometric procedure

The econometric procedure involved different steps like (a) validity of measuring instruments, (b) validity of constructs, (c) estimation of path coefficients, and (d) goodness of fit for PLS-SEM.

The validity of measuring instruments

The online questionnaire has been validated in the context of Pakistan by healthcare professional and academic staff members. According to experts, risk aversion and intention to prevent COVID-19 is required to control the spread of COVID-19 in Pakistan. Therefore, this study used risk aversion and the intention to prevent COVID-19 as endogenous variables. However, the healthcare professional and academic staff members give different suggestions for the improvement in COVID-19 related questions. Moreover, the relevant literature was also used to make this online questionnaire more comprehensive.

The validity of measuring constructs

The validity of constructs needs a clear definition with specified conceptual boundaries (Newman 2002) and concerned with the attributes instead of scores of the instrument (Salkind 2000). The validation used theoretical concepts to logically analyze and test the relationships. The validity of the construct has been tested using a convergent validity method. The word construct is a theoretical concept used to explain some phenomenon. The construct is a complex concept having several interrelated factors (Ghadi et al. 2012). In the present research, convergent validity was tested by factor loading, Composite Reliability (CR), and Average Variance Extracted (AVE) (Fornell and Larcker 1981). The Confirmatory Factor Analysis (CFA) estimates the factor loading of variables. This study used a total of 30 indicators (the questionnaire item). The acceptable factor load value is greater than 0.5 but it is considered good when it is equal or greater than 0.7 (Hair et al. 2010). Cronbach's alpha is also used to confirm the reliability of constructs (Ghadi et al. 2012). The CR is another indicator to confirm the convergent validity and its acceptable value is equal to or greater than 0.7 (Hair et al. 2010). The CR score is calculated using the following formula (Ghadi et al. 2012):

$$\mathrm{CR} = \frac{\left(\sum_{i=1}^{n} \lambda_{yi}\right)^2}{\left(\sum_{i=1}^{n} \lambda_{yi}\right)^2 + \left(\sum_{i=1}^{\rho} \mathrm{var}(\varepsilon_i)\right)} \tag{1}$$

where CR shows composite reliability, $\lambda_y$shows standardized factor loading, and $\mathrm{var}(\varepsilon_i)$ is the variance.

Another indicator, AVE is also used to confirm the reliability of constructs It measures the variance captured by a construct and variance due to measurement error. Its value should be equal or greater than 0.7 to reflect the reliability of a construct. However, its value above 0.5 is also acceptable (Hair et al. 2010). It is mathematically calculated using the following expression (Ghadi et al. 2012):

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n} \tag{2}$$

where AVE shows average variance extract, λ_i shows standardized factor loading, and n is the number of items.

The discriminant validity is also used to ensure that there is no significant variance between various constructs. Discriminant validity reflects the difference between one construct and another in the same model. Discriminating validity is asses by comparing AVE and the squared correlation between two constructs (Ghadi et al. 2012). The square root of AVE for each construct should be greater than the correlations of that construct with the other constructs in the model (Fornell and Larcker 1981; Assemi et al. 2018).

The partial least square-structural equation model

The regression coefficients were estimated using partial least square-structural equation model (PLS-SEM). The PLS-SEM is widely used for the analysis of structural equation modeling (Chin 1998; Tenenhaus et al. 2005; Vinzi et al. 2010; Assemi et al. 2018). It is a multivariate statistical model to simultaneously estimate all the structural paths between the variables using the conceptual model. This model is also appropriate because it maximizes the variance of endogenous constructs (Hair et al. 2017). Structural equation modeling generally deals with the relationships between various endogenous and exogenous and endogenous, often unobserved variables (latent variables), which are measured using a set of observed variables (indicators) (Wolf and Seebauer 2014; Assemi et al. 2018). The PLS-SEM estimates a network of causal relationships based on the theoretical model and can establish the link among different latent constructs (Assemi et al. 2018). The PLS-SEM is have been widely used to examine complex relationships between latent constructs (Fernández-Heredia et al. 2014; Chung and Kim 2015). The PLS-SEM analysis was performed using SmartPLS 3. The PLS-SEM regression estimates the parameters of the measurement model and latent variables (Rasoolimanesh et al. 2018). Latent constructs are unobserved concepts like intension to prevent COVID-19 and risk aversion, which are measured through different observed indicators such as the survey questions in this study. The PLS-SEM used a two-stage estimation procedure. The first stage deals with the estimation of the score of latent variables and outer loadings and outer weights for measuring constructs using a series of iterative steps (Hair et al. 2017). The second stage deals with the estimation of path coefficients between the latent variables using ordinary least squares (OLS) to maximize the variance (Lohmöller 1989). The maximizing of shared variance is the primary objective of PLS-SEM and other regression methods (Hair et al. 2017). The equation used for the estimation of PLS-SEM is expressed as (Kock 2010):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon_1 \tag{3}$$

The PLS-SEM used confirmatory factor analysis with path analysis and recognized as a soft modeling approach because it does not require strong assumptions about sample size, distribution, and measurement scale (Chin and Newsted 1999; Hair et al. 2010; Urbach and Ahlemann 2010; Assemi et al. 2018). The estimation of regression coefficients used a nonparametric bootstrapping procedure to determine the significance of association using resampling with replacement from the original sample (Hair et al. 2013). The bootstrapping gives probability values showing the stability of path coefficients (Andreev et al. 2009). This method examines the significance of the relationships between different constructs using an iterative algorithm based on the ordinary least squares estimation (Vinzi et al. 2010). The path coefficients in PLS-SEM reveal the validity of the hypotheses (Chung and Kim 2015). The significance of the path coefficient was determined using t-

Table 1 Demographic characteristics of participants ($N = 310$)

Characteristics	Frequency (n)	Percent (%)
Age (years)		
Below 25	117	37.74
25–40	167	53.87
41–60	21	6.77
Above 60	5	1.61
Gender		
Male	207	66.77
Female	103	33.23
Education		
PhD	45	14.52
Master/M.Phil	155	50.00
MBBS	56	18.06
Bachelor	47	15.16
Intermediate	06	1.94
Matriculations	01	0.32
Occupation		
Academic Staff	121	39.03
Non-Academic Staff	27	8.71
Healthcare Professional	56	18.06
Security Forces Personnel	03	0.97
Student	103	33.23

statistics and probability values. The t-statistic should be equal or greater than 1.96, and the probability score should be equal or less than 0.05, to determine the significance of regression coefficients.

The goodness of fit (GoF) of PLS-SEM was estimated using the geometric mean of the average AVE and average R^2 for the endogenous construct (Tenenhaus et al. 2005; Wetzels et al. 2009; Assemi et al. 2018):

$$\mathrm{GoF} = \sqrt{\overline{\mathrm{AVE}} \times \overline{\mathrm{R}^2}} \tag{4}$$

According to Wetzels et al. (2009), the GoF of PLS-SEM was interpreted using the baseline cut-off values, which are $\mathrm{GoF}_{small} = 0.1$, $\mathrm{GoF}_{medium} = 0.25$, and $\mathrm{GoF}_{large} = 0.36$.

Results and discussion

Demographic characteristics of respondents

Table 1 reveals different demographic characteristics of total 310 respondents. The respondents were categorized into four groups according to their age. Maximum respondents (53.87%) were young, having 25–40 years of age followed by less than 25 years (37.74%), 41–60 years (6.77%), and more than 60 years (1.61%). According to gender, 207 (66.77%) participants were male while 103 (33.23%) participants were female. This study also investigated the qualification of respondents, which showed that most of the respondents were qualified persons. About 50% respondents had Master/M.Phil degrees while 18.06% and 14.52% respondents had MBBS and Ph.D. degrees, respectively. Bachelor degree holders were 15.16% followed by intermediate (1.94) and matriculation (0.32%). This research also questioned about the occupation of respondents. Maximum (39.03%) were involved in teaching activities and categorized as academic staff while the share of respondents from the non-academic staff was 8.71%. The persons associated with the health sector were 56 (18.06%) while only 0.97% of respondents were security forces personnel. In the current situation of COVID-19 in Pakistan, the health sector and security forces personnel are continuously working for the safety of human beings.

Descriptive analysis of indicators (measured in Likert scale)

Table 2 shows the descriptive analysis of different COVID-19 rerated aspects using Likert scale questions for each aspect (Table 3). The score of risk aversion was 4.555 which lies between strongly agree value (5) and agree value (4), which implies that the situation of risk aversion is better in Pakistan. The intention to adopt preventive measures is also important to control COVID-19 in a country, showing an average value of 4.463 which lies between the strongly agree (5) and agree (4) responses. The knowledge about COVID-19 can play a positive role to detect the patients and prevent this disease.

Table 2 Descriptive analysis of indicators (measured in Likert scale)

Constructs	Mean	Minimum	Maximum	SD
Risk aversion (RA)	4.555	3.200	5.000	0.442
Intention to prevent COVID-19 (IPC)	4.463	3.000	5.000	0.464
COVID-19 knowledge (COK)	4.612	3.286	5.000	0.422
Behavioral control (BC)	4.322	2.000	5.000	0.623
Moral and subject norms (MSN)	4.513	2.000	5.000	0.458
Preventive e-guidelines (PEG)	4.329	2.000	5.000	0.577
Environmental factors (EF)	4.455	2.000	5.000	0.593

Table 3 The question-wise response of participants (percentage)

Constructs/measurement items	Strongly disagree	Disagree	Uncertain	Agree	Strongly agree
Risk aversion (RA)					
(RA_1) I am adopting preventive measures to keep myself healthy.	0.65	0.65	1.94	41.29	55.48
(RA_2) I am adopting preventive measures to keep my kids/parents/siblings/spouse healthy.	---	---	1.29	36.45	62.26
(RA_3) I am advising my kids/parents/siblings/spouse to adopt preventive measures.	---	0.32	1.61	40.97	57.10
(RA_4) I am avoiding visits to crowded places and staying at home.	---	0.32	1.94	37.10	60.65
(RA_5) I am practicing social distancing.	0.65	0.32	2.58	37.74	58.71
Intention to prevent COVID-19 (IPC)					
(IPC_1) I intend to adopt preventive measures if any outbreak happens in the future.	---	0.97	4.19	50.00	44.84
(IPC_2) I am ready to be quarantined to prevent the outbreak of the pandemic.	---	0.32	4.52	43.23	51.94
(IPC_3) I am intent to highly recommend preventive measures to others.	---	0.32	3.23	40.32	56.13
(IPC_4) I have the intention to adopt a healthy lifestyle even after the outbreak.	---	1.94	4.19	42.90	50.97
(IPC_5) I intend to adopt preventive measures during the present outbreak.	---	0.32	2.26	43.55	53.87
COVID-19 knowledge (COK)					
(COK_1) The COVID-19 may transmit through human to human interaction.	---	---	0.97	30.65	68.39
(COK_2) The COVID-19 may transmit through a common contact point like ATMs and doors	---	1.29	3.87	36.77	58.06
(COK_3) The COVID-19 may transmit through handshake and communication with the carrier.	---	0.65	2.26	30.00	67.10
(COK_4) Symptoms of COVID-19: fever, dry cough, sneezing, body aches and breathing issue.	---	---	1.94	34.84	63.23
(COK_5) The COVID-19 may be prevented if we keep ourselves clean/hand washing.	---	0.65	2.58	33.23	63.55
(COK_6) The COVID-19 enters the human body through the nose, mouth, and eyes.	---	---	1.61	32.26	66.13
(COK_7) The COVID-19 can be prevented through social distancing.	---	0.32	2.90	32.58	64.19
Behavioral control (BC)					
(BC_1) I have the skills to adopt preventive measures.	0.65	3.87	6.13	44.52	44.84
(BC_2) I can completely adopt preventive measures.	---	3.55	9.03	38.71	48.71
(BC_3) I believe I will adopt these measures until the outbreak persists.	---	2.90	7.10	42.26	47.74
Moral and subject norms (MSN)					
(MSN_1) I am adopting preventive measures as they are suggested by health professionals.	---	2.58	1.94	43.87	51.61
(MSN_2) I have suggested my colleagues, friends, and neighbors to adopt preventive measures.	---	0.97	4.19	41.94	52.90
(MSN_3) I am morally responsible to prevent others from being infected if I am infected.	0.65	0.32	1.29	37.74	60.00
(MSN_4) It is my moral obligation to provide masks and disinfectants to others in case of access.	---	0.97	3.55	38.06	57.42
(MSN_5) If I have any symptoms. I am responsible to inform the relevant health authorities.	---	2.26	1.94	38.71	57.10
(MSN_6) I am responsible to adopt preventive measures not only for myself but also for others.	---	0.97	2.58	33.87	62.58
Preventive e-guidelines (PEG)					
(PEG_1) The prevention e-guidelines by the government are clear and simple.	0.97	0.65	5.81	45.16	47.42
(PEG_2) The prevention e-guidelines by the government are positive.	0.65	1.29	4.52	50.65	42.90
(PEG_3) The prevention e-guidelines by the government have motivational appeals.	0.32	1.94	9.68	48.06	40.00

Table 3 (continued)

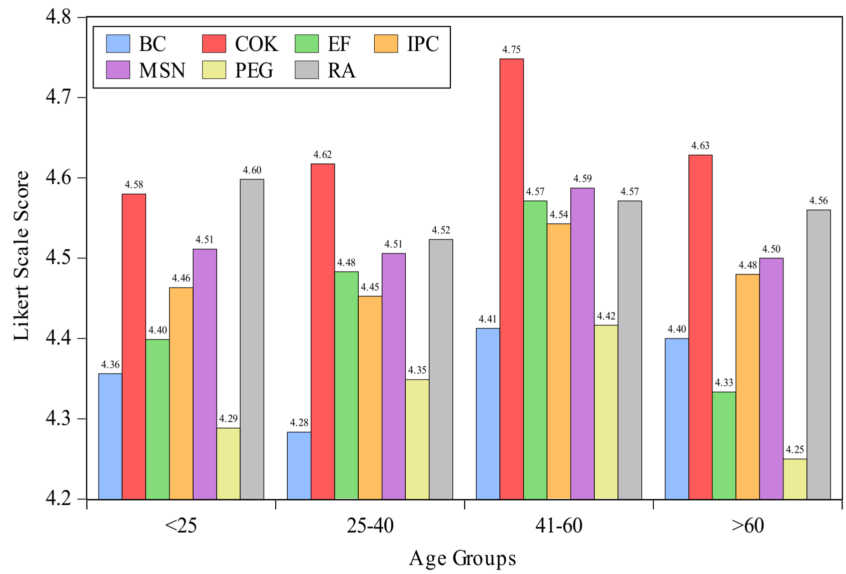
Constructs/measurement items	Strongly disagree	Disagree	Uncertain	Agree	Strongly agree
(PEG_4) e-Guidelines by the government were primary source of adopting preventive measures.	0.65	1.61	5.48	46.77	45.48
Environmental factors (EF)					
(EF_1) I think COVID-19 spread depends upon environmental factors (temperature, humidity, precipitation, etc.)	---	2.90	3.55	41.29	52.26
(EF_2) I think that the use of face masks to prevent COVID-19 is difficult in the summer season.	---	4.52	4.52	40.97	50.00
(EF_3) I think that COVID-19 transmission reduced by the increase in temperature.	---	1.94	5.16	36.77	56.13

The score of COVID-19 knowledge was 4.612 on the Likert scale, which implies that most of the respondents had knowledge of COVID-19 in Pakistan. The intention to prevent COVID-19 also depends upon the behavior and moral norms of respondents. The Likert scale score of behavior control and moral and subject norms was 4.322 and 4.513, respectively. It shows that score of moral norms was higher than behavior control. The e-guidelines about COVID-19 prevention by the government could also influence the prevention behavior of a person. According to respondents, the score of e-guidelines was 4.329 (Likert scale), which shows that it is more close to the "agree" response (4). Therefore, it is possible to further improve the e-guidelines for COVID-19 prevention. The score of environmental factors was 4.455 on the Likert scale, which implies that most of the respondents linked environmental factors with the COVID-19 pandemic.

Mean of indicators by age, gender, qualification, and occupation

This study used seven COVID-19 related constructs (risk aversion, intention to prevent, knowledge, behavioral control, moral and subject norms, and e-guidelines). Figure 2 explores the average of each construct for different age groups. The less than 25 years old respondents had higher value for risk aversion (4.598). The respondents belong to age group 41–60 years had higher values for knowledge of COVID (4.748), behavioral control (4.413), moral and subject norms (4.587), preventive e-guidelines (4.417), intention to prevent COVID-19 (4.543), and environmental factors (4.571). The e-guidelines score was less for the persons with more than 60 years of age and risk aversion was less for the age group 25–40 years. Figure 3 explains the situation of COVID-19 related indicators among male and female respondents. It is cleared that female respondents had higher COVID-19 knowledge (4.691), moral and subject norms (4.584), preventive e-guidelines (4.396), intention to prevent COVID-19 (4.507), risk aversion (4.631), and environmental factors (4.498). On the other hand, male respondents had a higher score for behavioral control (4.3317). According to Fig. 4, the respondents having an MBBS degree had a higher score for behavioral control (4.69), intention to prevent COVID-19 (4.66), and environmental factors (4.608). The respondent having matriculation degrees had a higher score for COVID-19 knowledge (4.86), prevention e-guidelines (4.75), and risk aversion (4.80). The moral and subject norms score was higher (4.72) for the respondents holding an intermediate degree. Figure 5 reveals the COVID-19 related indicators according to the occupation of respondents. The respondents from the healthcare department had a higher score for behavioral control (4.399), moral and subject norms (4.548), and preventive e-guidelines (4.420). Respondents who belong to the academic department had a higher score for COVID-19

Fig. 2 COVID-19 indicators by age groups

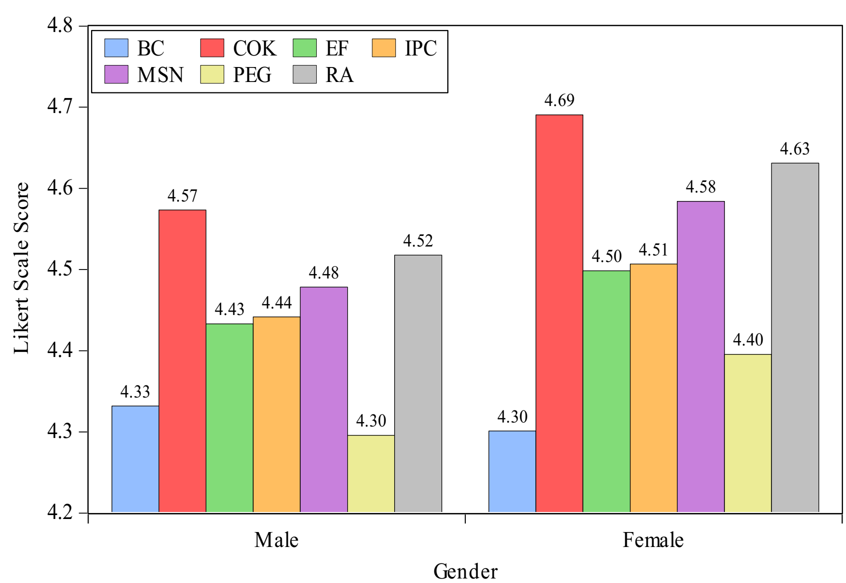


knowledge (4.634), intention to prevent COVID-19 (4.499), and risk aversion (4.579).

The question-wise response of participants

Table 3 shows the response of COVID-19 related questions, using the Likert scale (strongly agree, agree, uncertain, disagree, and strongly disagree). The frequency analysis shows that 55.48% respondents strongly agreed to the adoption of preventive measures while 41.29% respondents agreed to the adoption of preventive measures. About 62.26% respondents strongly agreed to the adoption of preventive measures for the safety of their kids, parents, siblings, and spouse while 57.10% respondents strongly agreed that they are advising their kids, parents, siblings, and spouse to adopt preventive measures. About 60.65% respondents strongly agreed that they are avoiding the visits to crowded places and staying at home. Social distancing is recommended to slow down the COVID-19 spread, and 58.71% respondents strongly agreed that they are practicing social distancing. About 56.13% respondents strongly agreed with the statement that they are recommending the preventive measures to others while 51.94% participants strongly agreed that they are ready to be quarantined to prevent the COVID-19 outbreak. Investigating about the COVID-19 related knowledge, 68.39% respondents strongly agreed that the COVID-19 may transmit through human to human interaction while the percentage was 58.08% who strongly agreed that the COVID-19 may transmit through the common contact point. About 67.10% respondents strongly agreed that COVID-19 may transmit through a handshake

Fig. 3 COVID-19 indicators by gender



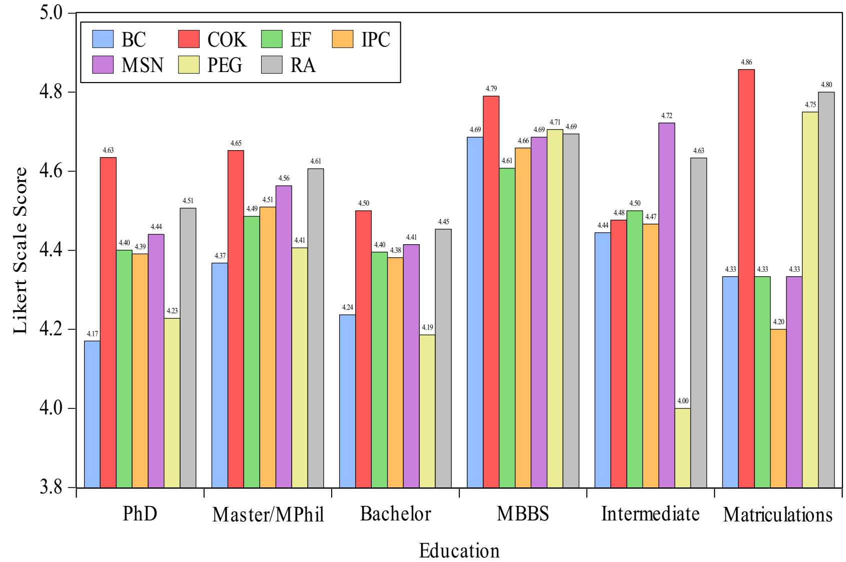


Fig. 4 COVID-19 indicators by educational qualification

with the carrier. On the other hand, 63.55% respondents strongly agreed that COVID-19 can be prevented through continual hand washing. Less than 50% respondents strongly agreed about the behavioral control indicators to prevent COVID-19. About 60% respondents strongly agreed to the statement that they are morally responsible to prevent others from being infected if they are infected. About 51.61% participants strongly agreed that they are taking preventive measures as they are suggested by health professionals. However, less than 50% of participants strongly agreed to the statements about the preventive e-guideline by the governments. More than 50% respondents strongly agreed to the statement that the COVID-19 spread depends upon environmental factors like temperature, humidity, and precipitation. About 50% respondents think that the use of face masks is difficult in the summer season. More than 55% respondents believed that the COVID-19 transmission may reduce due to the increase in temperature.

Assessment of the measurement model

The PLS regression was used to empirically estimate the influence of COVID-19 knowledge, behavioral control, moral and subject norms, preventive e-guidelines by the government, and environmental factors on the intention to prevent COVID-19 and risk aversion. In PLS analysis, the first step is to check the reliability of different COVID-19 related constructs (Table 4). Table 4 shows the loading value of each measurement items (questions), which reflects the association between the measurement item and the respective construct.

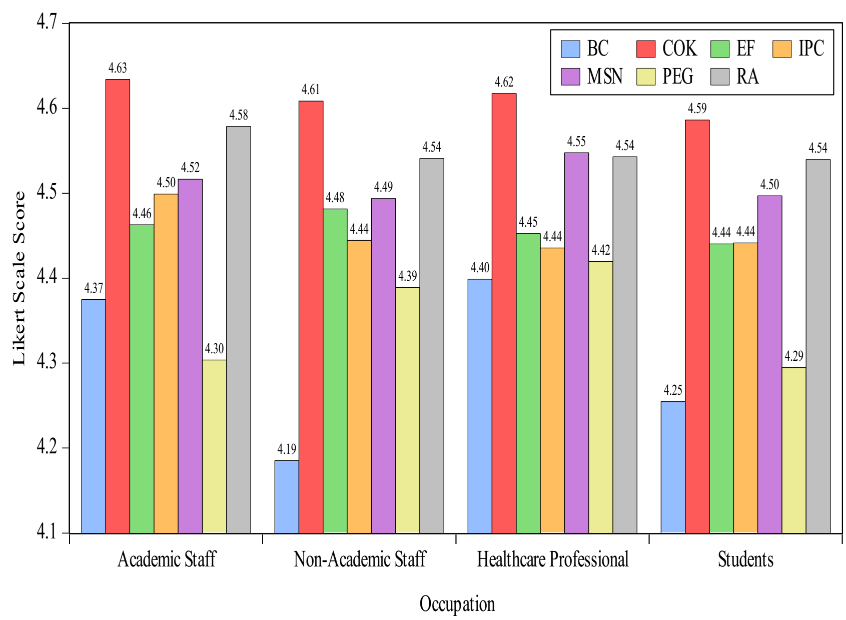


Fig. 5 COVID-19 indicators by occupation

Table 4 Assessment of the measurement model

Constructs/measurement items	Loading	Cronbach-α	ρ-A	CR	AVE
Risk aversion (RA)					
RA_1	0.708	0.828	0.830	0.880	0.595
RA_2	0.809				
RA_3	0.832				
RA_4	0.776				
RA_5	0.725				
Intention to prevent COVID-19 (IPC)					
IPC_1	0.788	0.825	0.830	0.877	0.588
IPC_2	0.729				
IPC_3	0.795				
IPC_4	0.790				
IPC_5	0.729				
COVID-19 knowledge (COK)					
COK_1	0.791	0.882	0.884	0.908	0.587
COK_2	0.724				
COK_3	0.700				
COK_4	0.826				
COK_5	0.735				
COK_6	0.787				
COK_7	0.790				
Behavioral control (BC)					
BC_1	0.763	0.729	0.730	0.847	0.648
BC_2	0.830				
BC_3	0.821				
Moral and subject norms (MN)					
MSN_1	0.698	0.825	0.829	0.872	0.533
MSN_2	0.761				
MSN_3	0.765				
MSN_4	0.721				
MSN_5	0.708				
MSN_6	0.722				
Preventive e-guidelines (PEG)					
PEG_1	0.833	0.826	0.838	0.885	0.658
PEG_2	0.856				
PEG_3	0.751				
PEG_4	0.800				
Environmental factors (EF)					
EF_1	0.816	0.795	0.817	0.879	0.707
EF_2	0.838				
EF_3	0.868				

As a rule of thumb, the loading value of each measuring item must be equal or more than 0.7 to confirm the reliability of the measurement model (Hair et al. 2017; Rasoolimanesh et al. 2018). Table 4 confirms that the loading value of each measurement indicator was greater than 0.7, which implies that the construct used in PLS analysis was reliable. The items having less than 0.5 loading value should be removed, the loading values lie between 0.5 and 0.7 can be removed if their removal increases the Average Variance Extracted (AVE) and Composite Reliability (CR) above the threshold (Hair et al. 2017). For the reliability of a construct, this study also used CR whose acceptable value is greater than 0.7 (Hair et al. 2017). The CR statistics also confirmed the reliability of selected constructs because the CR statistics value was greater than 0.7 for each case. For, convergent validity, the cut-off AVE values of the latent constructs should be greater than 0.5

Table 5 Correlations and discriminant validity results

Constructs	RA	IPC	COK	BC	MSN	PEG	EF
RA	*0.771*						
IPC	0.705	*0.767*					
COK	0.586	0.501	*0.766*				
BC	0.483	0.476	0.314	*0.805*			
MSN	0.713	0.644	0.494	0.553	*0.730*		
PEG	0.517	0.550	0.408	0.441	0.561	*0.811*	
EF	0.454	0.380	0.275	0.312	0.674	0.365	*0.841*

The italicized diagonal shows the square root of each latent variable

(Hair et al. 2017). The AVE results also showed the reliability of the measurement model, as AVE values for all contracts were greater than 0.5. According to Bortoleto et al. (2012), the reliability of a construct also depends upon the internal consistency of the construct. Therefore, Cronbach-α, ρ-A, and composite reliability (CMPR) were also used to check internal consistency. For these reliability indicators, the acceptable range was between 0.7 and 0.95 (Elmustapha et al. 2018). For the reliability of the construct, the value of ρ-A should lie between Cronbach-α and CR (Lopes et al. 2019). These indicators also confirmed the reliability of the construct in this study.

The discriminating validity reflects the distinction between two latent variables (Chin 2010). As a rule of thumb, the square root of the AVE for each latent variable should be greater than the score of correlation with all other latent variables in the model (Fornell and Larcker 1981; Rasoolimanesh et al. 2018). Table 5 shows the square root of each latent variable in italicized diagonal, which is greater than the correlations score for other latent variables. The square root of risk aversion was 0.771, which is higher than the correlation score of risk aversion with the intention to prevent COVID-19 (0.705), COVID-19 knowledge (0.586), behavioral control (0.483), moral and subject norms (0.713), preventive e-guidelines (0.517), and environmental factors (0.454). Therefore, the measurement model confirmed discriminant validity using COVID-19 related constructs or latent variables.

Partial least square regression

After the confirmation of the reliability of constructs, the next step is to explore the regression coefficients using the PLS structural equation model. The significance of the path coefficient was confirmed using t-statistics and probability values. This research assumed that the COVID-19 knowledge, behavioral control, moral and subject norms, preventive e-guideline, and environment are influencing factors behind the intention to prevent COVID-19. The intention to prevent COVID-19 leads to risk aversion, which is required to control the spread of COVID-19. However, the indirect effect also explores the influence of COVID-19 knowledge, behavioral control, moral and subject norms, preventive e-guideline, and environmental factors on risk aversion. Table 6 demonstrates that all the influencing factors, excluding environmental factors, had a significant and positive impact on the intention to prevent COVID-19 and risk aversion. Moral and subject norms had a comparatively higher path coefficient (0.359), which implies that the influence of moral and subject norms is higher in society. It showed that the moral values are an important component of Pakistani society. According to influencing score,

Table 6 Regression results of PLS model

Hypothesis	Hypothesized path	Path coefficients	Standard deviation	T-stat.	*P* value	Decision	Driver/barrier
Total direct effects							
H_1	COK → IPC	0.193*	0.052	3.733	0.000	Supported	Driver
H_3	BC → IPC	0.116**	0.054	2.140	0.033	Supported	Driver
H_5	MSN → IPC	0.405*	0.060	6.719	0.000	Supported	Driver
H_7	PEG → IPC	0.215*	0.061	3.517	0.000	Supported	Driver
H_9	EF → IPC	− 0.061	0.046	1.326	0.185	Not supported	-----
H_{11}	IPC → RA	0.705*	0.034	20.545	0.000	Supported	Driver
Total indirect effects							
H_2	COK → RA	0.136*	0.039	3.480	0.001	Supported	Driver
H_4	BC → RA	0.082**	0.038	2.125	0.034	Supported	Driver
H_6	MSN → RA	0.286*	0.046	6.200	0.000	Supported	Driver
H_8	PEG → RA	0.152*	0.042	3.598	0.000	Supported	Driver
H_{10}	EF → RA	− 0.043	0.032	1.333	0.183	Not supported	-----
The goodness of fit (model**)**							
R^2 (IPC)	0.508	R^2 (RA)	0.497	Goodness of fit (GoF)		0.556 (model is good)	

[*] shows the significance at 1%; [**] shows the significance at 5%

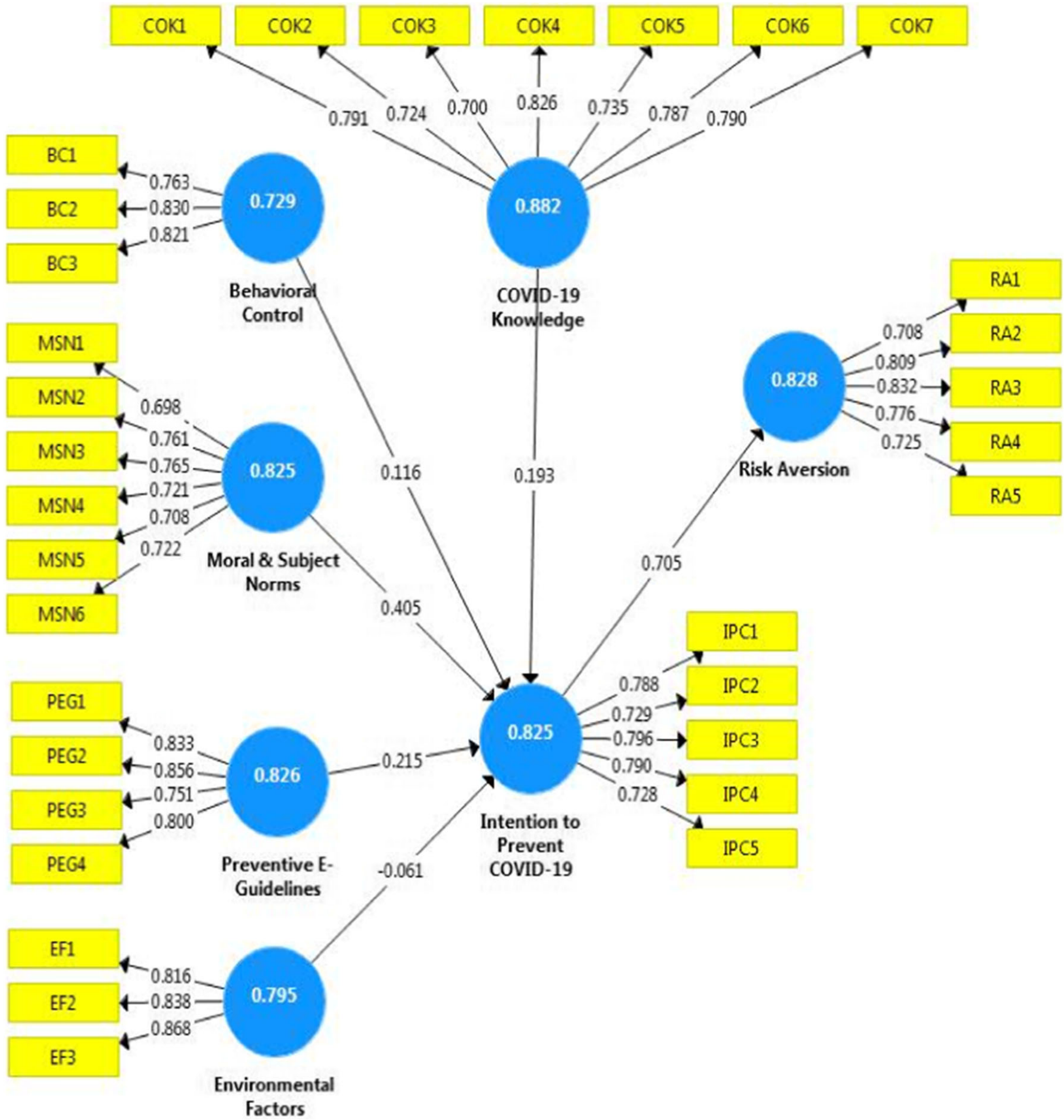


Fig. 6 Results of PLS structural model

the preventive e-guideline by the government ranked second (0.215), which implies that preventive e-guideline by the government acts as a driver to increase the intention to prevent COVID-19. A positive and significant influence was also confirmed in the case of COVID-19 knowledge, whose path coefficient was 0.197. It means that the increase in COVID-19 knowledge could be beneficial for the intention to prevent COVID-19. The comparatively low value of the path coefficient was observed in the case of behavioral control (0.112). The risk aversion is required to break the chain of viral infection. The intention to prevent COVID-19 showed a positive and significant impact (0.705) on risk aversion. During the infectious outbreak, the role of each individual is important to control its spread. The impact of environmental factors on intention to prevent COVID-19 was negative and insignificant, which implies that the environmental factor does not significantly influence the intention to prevent COVID-19. Table 6 also reveals the indirect impact of influential factors on risk aversion. According to the indirect impact analysis, all influencing factors, excluding environmental factors had a significant and positive impact on risk aversion. In line with direct impact, the indirect impact of moral and subject norms had a higher path coefficient (0.139), which implies that the influence of moral and subject norms on risk aversion. The preventive e-guideline by the government ranked second (0.151), which implies that preventive e-guideline by the government acts as a driver to increase the risk aversion. A positive and significant influence was also confirmed in the case of COVID-19 knowledge, whose path coefficient was 0.139. It means that the increase in COVID-19 knowledge could be beneficial for the risk aversion. The comparatively low value of the path coefficient was observed in the case of behavioral control (0.085). The impact of environmental factors on risk aversion was negative and insignificant, which implies that the environmental factor does not significantly influence the risk aversion behavior. The goodness of fit for the model was also explained using R-square, which shows variance accounted by every endogenously found construct and validated the prediction capability of the model. The R-square value should be greater than 0.25 for appropriate results (Davison and Hinkley 1997). This study showed that the R-square value was 0.508, which is higher 0.25, and confirmed the prediction capability of the structural model.

Figure 6 describes the framework of the PLS structural equation model using different influencing factors to control the spread of COVID-19. The yellow boxes are the measurement indicators (question) of each construct. The values between yellow boxes and the blue circle show the loading values of each indicator, which are greater than 0.7, showing the reliability of indicators. The value inside the blue circle is the Cronbach-α value, which is greater than 0.7 for all constructs, showing the reliability of each construct in the model. The values between two blue circles explain the regression coefficients, which are all significant.

Conclusions and policy implication

COVID-19 becomes a major threat to public health and the global economy, which also affects the lives of human beings. The adoption of a preventive measure by the general public is required to control the spread of epidemics. In the case of the current pandemic, the implication of the personnel protective measures is only feasible if the community is well aware of the COVID-19 knowledge and responds positively towards the preventive e-guidelines by the government. This research explores the impact of influencing factors like COVID-19 knowledge, behavioral control, moral and subject norms, preventive e-guidelines by the government, and environmental factors on the intention to prevent COVID-19 and risk aversion. This study used an online survey method to get information from 310 respondents. Moral and subject norms had a comparatively higher path coefficient, which implies that the influence of moral and subject norms in society. The preventive e-guideline by the government ranked second, which implies that preventive e-guideline by the government acts as a driver to increase the intention to prevent COVID-19. A positive and significant influence was also confirmed in the case of COVID-19 knowledge, which implies that the increase in COVID-19 knowledge could be beneficial for the intention to prevent COVID-19. The comparatively low value of the path coefficient was observed in the case of behavioral control. However, the impact of environmental factors was negative and insignificant on the intention to prevent COVID-19. The intention to prevent COVID-19 showed a positive and significant impact (0.705) on risk aversion. The indirect impact analysis also confirmed that all influencing factors, excluding environmental factors, had a significant and positive impact on risk aversion in Pakistan. The indirect impact of moral and subject norms had a higher path coefficient. The COVID-19 knowledge, preventive e-guideline by the government, and behavioral control had a positive and significant influence on risk aversion. It is suggested to the government to give clear guidelines related to COVID-19 prevention using print, social, electronic media. The e-guidelines are also necessary to counter the fake news, especially circulating on social media. It is also suggested to provide e-guidelines in local languages as well. The knowledge related to COVID-19 about its transmission, symptoms, and precautions is also useful. The COVID-19 is a driver behind the intention to prevent and risk aversion in Pakistan. It is suggested to ensure the awareness of pandemic among the general population. The government should include the causes, symptoms, and precautions related to various viral diseases in the educational syllabus. The government should ensure the availability of preventive medical items like surgical masks and sanitizers to meet the demand of the public. It is also recommended to guide the general population about the use of protective items like face masks and sanitizers. The behavioral control increases when a person is well aware of the use of preventive items and confidently follows the preventive measures. It is also recommended to guide the general population using moral values. It is recommended that the government should morally encourage the people having COVID-19 symptoms and encourage them to immediately contact health personals.

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